When will I see you again: modelling the influence of social networks on social activities

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***Abstract*—Social activities account for a large amount of travel, yet due to their irregularity and the number of options regarding location, participants, and timing, they are difficult to model and predict. We assume that social activities are constrained by one's social network, which consists of people you are close to, both socially and spatially. Therefore, a model of social activity behaviour should be sensitive to the network. In this paper, an agent-based model to describe social activities between two people over time is described and four different input networks (random, based on spatial distance, based on social distance, based on both distances) are experimented with. The results show that the overall social network has an effect on the number of activities generated in the entire system and also between pairs of friends.**

I. Introduction

Every transport system may be described as a social system, composed of individuals who interact and influence the behaviour of each other. Multi-agent simulation is therefore becoming increasingly important in travel simulation, travel analysis, and travel forecasting, in particular due to its possibilities to model explicitly the individuals' decision making processes. In fact, all travel is a result of individual decisions, as people try to manage his/her life in a satisfying way. As such, travel can be seen as result of individual goals (e.g. go to work to earn money, visit friends for pleasure) [1].

Our focus in this paper is on social face-to-face activities. People frequently interact face-to-face with each other. This could fulfill several needs: to gather information, to share an experience, to help one another, or for relaxation. Face-to-face interaction is sometimes also crucial for relationships to continue. Urry [2] notes that "[e]specially in order to sustain particular relationships with a friend or family or colleague that are 'in the mind', that person has intermittently to be seen, sensed, through physical copresence".

In order to model these activities, the transport modelling field is experiencing a shift from understanding "where are people going" and "what activity are they doing" towards "who are they interacting with". The generation and scheduling of social activities depends not only on the structure of the spatial network, which is covered by "where" and "what", but requires that social networks, which mean "who" need to be incorporated as well.

In this project, we are interested in ascertaining the influence of social network typology on the number, frequency and type of social activities between network nodes. This is necessary because incorporating social networks into existing activity-travel models will add a lot of complexity and require more intensive data collections. Testing the sensitivity of potential models of activity behaviour to different networks is an important step in evaluating the usefulness of their incorporation.

The aim of this paper is to demonstrate the relevance of the social network structure, by investigating the performance of a simplified model with different input structures with respect to the number of activities generated for individuals, pairs of individuals, and for the entire population. We begin with a review of activity modelling and social network generation. A model with utility-based agents is described and the results are discussed. We conclude with recommendations for other applications and future work.

II. Background and related work

A. Activity generation

Human activities are generated due to "physiological, psychological and economical needs" [3]. A distinction is commonly made between subsistence (e.g., work-related), maintenance (e.g., keeping the household running), and leisure activities.

Non-discretionary activities such as work and school can be partly explained by the traveller's sociodemographic characteristics and generalised travel costs [4], as well as long-term decisions such as a decision to move to a particular town. Participation in, and scheduling of, other activities is not as easily predicted. Social and leisure activities are the reported purpose for a large number of trips, ranging from 25 to 40% for various countries [5].

In current state-of-the-art activity-travel models, social activities, if at all scheduled, are assigned to random locations and times [6] and do not take into account the constraints or preferences of friends. Being able to model these activities could lead to better prediction of activity schedules and forecasts of travel patterns and demand for urban facilities, in particular those relating to social and leisure activities.

A theory currently being explored for generating discretionary activities is based on needs. Activities both satisfy and generate needs and needs grow over time [7]. Maslow's hierarchy of needs has been proposed as a starting point [8], however it is difficult to collect data for model validation. A separate set of needs was proposed by Arentze and Timmermans [7] which could be identified through empirical research.

B. *Social networks*

Social networks are a representation of individuals and the relationships between them. The relationship between two individuals can be defined in a number of ways, for example how similar they are, how they are related to each other, whether they interact or how often they interact, or how information flows between them [9].

Networks can be represented in two ways: complete or personal. A complete network contains all of the relationships for all the individuals in the network, for example, all the friendship links between students in a class. Personal networks contain the relationships for a particular individual (known as the ego), however the attributes of the people they name (known as alters) are provided by the ego rather than the alter themselves. It is not guaranteed that the personal networks of egos in the sample will intersect.

As Newman [10] recognised, research has been slow in understanding the actual workings of networked systems and the focus has been on structural form and analysis. As a result, there are many methods for generating (e.g., the small world model [11] and the scale-free network [12]) and measurements for comparing static, complete (and not necessarily social) networks (e.g., [13]). However, it has been recognised that social networks have certain properties, in particular with respect to the similarity between people, their spatial proximity, the overall clustering coefficient (i.e., how tightly-knit the network is) and the variation in size of personal networks (e.g., how many friends do people have; also known as the degree). Hamill and Gilbert [14] presented a model known as social circles, where two people are connected depending on the distance between them. This distance could be social (e.g., based on whether two people are similar in terms of age, gender, occupation, religion, or shared values etc.) or spatial.

C. *The effects of social networks on activities*

The bulk of the research on the effects of social networks on activities is at the data analysis stage. Individuals are surveyed about their social network and asked to complete an activity diary for several days, listing who they interacted with and the nature of the activity.

As part of the Connected Lives study, Carrasco [15] collected data on individuals' personal networks and interactions, then used multi-level modelling to look for influences on frequencies of activities. The results showed that the number of components (i.e., subgroups), density (i.e., clustering), and degree of the personal network influences the frequency of social interactions, and are a better indication of frequency than the size of the network or isolates. Younger people tend to have a higher frequency of activities, as well as egos and alters with similar ages.

The latter is an example of homophily, which is based on the idea that individuals interact with others who are similar to them [16]. Homophilies can be separated into two groups: those based on status, both ascribed (e.g., age, gender, etc.) and acquired (e.g., occupation, religion, etc.), and those based on values, such as attitudes and beliefs.

Given the data collected for activity-travel modelling purposes, at least two network generation algorithms have been developed. Illenberger et al. [17] presented a model based on spatial distance, while Arentze and Timmermans [18] developed an algorithm based on spatial and social distance. The latter can also be extended to include the influence of common friends, following the theory that if person 1 is friends with person 2 and person 3, then persons 2 and 3 have a good chance of also being friends.

Hackney and Marchal [19], building on previous work, developed a microsimulation which incorporated a social network on top of a daily activity scheduler. The individuals in the system exchange information with each other, either about locations or about friends. Currently their system does not include collaborative scheduling.

III. MODEL DESCRIPTION AND DESIGN

Joint social activities are defined by the different people involved, their relationships and interactions with each other, and their activities in and possible movement around the environment. The topology of interactions is not homogeneous and clusters may form. Therefore agent-based modelling appears to be appropriate for our model, due to the complex relationships and interactions between individuals and the individuals' situatedness in an urban environment [20].

The model consists of agents located in a spatial environment, where they have a home location. This environment is represented by a network of locations. Each agent has a list of other agents he/she is friends with and a list of locations that he/she knows. They also have sociodemographic attributes (e.g., age, gender, car ownership, work status etc.) and a schedule with a certain number of time periods. Each agent can undertake maximally one activity per time period.

Each pair of agents has a similarity measure, which follows from the notion of homophily. Pairs also keep track of when they last saw each other. Links are undirected, meaning that friendships are mutual.

The goals of the agents in the system are derived from the social needs of humans, which include interacting with, and gaining the respect and esteem of others. The agent goals are therefore:

- making and maintaining (long-term) relationships with other people;
- sharing experiences with other people, in the form of joint activity participation;
- sharing (giving and gaining) information with other people; and
- learning about their local environment.

In this paper we focus on the second goal of joint activity participation. Utility-based agents are used as this allows the agents to evaluate the outcomes of participating in different activities. This has advantages and disadvantages: utility functions are difficult to develop and tend to oversimplify the real-world processes [21], however as the aim is to create a model of a sample population for a city, i.e., thousands of agents, the agent model needs to be simple in order to be scalable.

A utility function (Equation 1) has been developed to take into account the required issues – type (a) and purpose (p) of the activity, location (l), day (d), the other person involved (j) –, essentially, what, where when and who. This is based on the needs-based theory discussed in Section II-A.

$$
\begin{aligned}
U_i(a,p,l,d,j) &= V_i^{ap} + V_i^l + V_i^j + \epsilon && (1)\\
V_i^{ap} &= f_t(\alpha_i^{ap}, d - t_{ap}) && (2)\\
V_i^l &= f_t(1 - d_{il}, d - t_l) && (3)\\
V_i^j &= f_t(s_{ij}, d - t_j) && (4)\\
f_t(x,t) &= (\frac{2}{1+e^{-xt}}) - 1 && (5)\\
s_{ij} &= Q_g + Q_a && (6)
\end{aligned}
$$

Activities can have a purpose, chosen from sharing experiences, sharing information, informal chatting, and support. The different purposes can be used to determine who is suitable for a given activity. Activities can also have a type, such as shopping, eating out, or sporting activities, which determines the location of the activity. In future, this will be also used to determine the duration of the activity.

The components of the utility function U_i consider when an individual last undertook an activity (Equation 2), visited a location (Equation 3), or saw someone (Equation 4). These values (t_l, t_{ap}, t_j) are combined with the date of the proposed activity d to find the last time the particular event happened. The utility increases over time (Equation 5), so that an activity/location/person that an individual hasn't seen/visited for a while is more attractive than one seen/visited the previous day.

The preferences for an activity with a particular purpose and type (α_i^{ap}) is also an input to the model. In this instance of the model, we consider preferences to be unidimensional as a simplification. It could be that preferences are dependent on the composition of the group, for example, in terms of gender, cultural background, size of the group etc.

The distance to the location (d_{il}) is also taken into account, based on the individual perception of the environment and travel time. For each pair of individuals i and j, a similarity measure was calculated (Equation 6), taking into account age (a) and gender (g). The values of d_{ij} and s_{ij} are scaled to $[0, 1]$.

In order to schedule activities, the agents need to negotiate with each other. This can be done using a negotiation protocol. Given that our aim is to understand the relation between social network and activities, we are more interested in the group formation than on the specific time and type of activity undertaken. As such, we use the package deal method [22] that abstracts from negotiation issues (for example, the activity may determine the time and location or vice versa, or in which order they should be discussed).

We further assume that interactions and activities are undertaken between two agents, who are connected to each other in the social network. This means that the social and location networks do not change (as new connections are not being made), therefore the centrality calculations do not change.

Agent i, the host, makes a decision to start an interaction using an altered utility function, where the initial location l is set to the other agent's (j; the participant) house:

$$
\begin{aligned}
U_s(a,p,l,d,j) &= V_i^{ap} + V_i^j + V_i^{jl} && (7)\\
V_i^{jl} &= f_t(1 - d_{il}, t_j) && (8)
\end{aligned}
$$

If U_s exceeds i's threshold, the host and participant exchange ideas for days and locations.

1) Host proposes an activity.
2) The respondent then creates a list of the possible day/time combinations (taking into account the host's time window) and sends them to the host.
3) The host collates the day/times and creates a list of the *intersection* of the suggestions.
4) The respondent determines what type of locations are appropriate from the patterns provided. They then look up which locations they know of that match those location types.
5) The host collates the locations and creates a list of the *union* of the suggestions.
6) The host then creates a list of possible activities, taking into account when agents are available and the locations they have suggested. The list is returned to the respondent.
7) The respondent evaluates this list using a utility function and returns the list with their preferences.
8) Using the Borda ranking method, the host determines the chosen option and notifies the respondent, who adds the activity to their schedule. The host also adds the activity to their schedule.

Negotiations can be unsuccessful if neither individual is available on the same day, neither can suggest any suitable locations, or one individual finds that the utility of all proposed activities does not exceed their threshold.

IV. Network inputs

For all input networks, the agent population was constant, with the same personal properties (age, gender), thresholds and parameters, and home location. The average degree was kept roughly the same ($\sim$10), which is in line with analysis of friendship/social interaction networks [18].

Four different networks were generated. The first was a random graph based on Erdos-Renyi random graph [23], randomly generated by the NetworkX package for Python [24]. This network is shown in Figure 1.

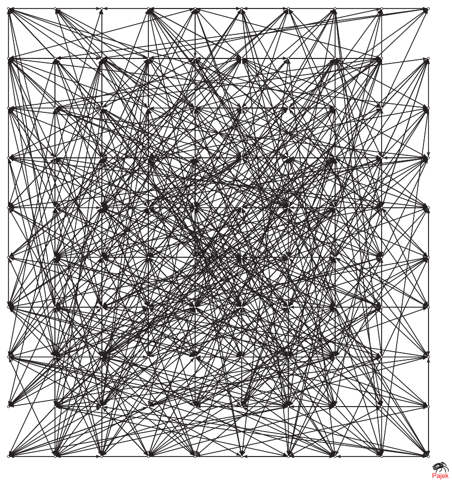

Fig. 1. The random network.

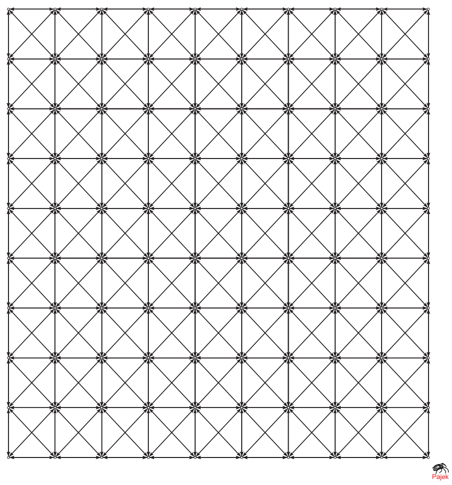

Fig. 2. The social circles network taking into account spatial distance.

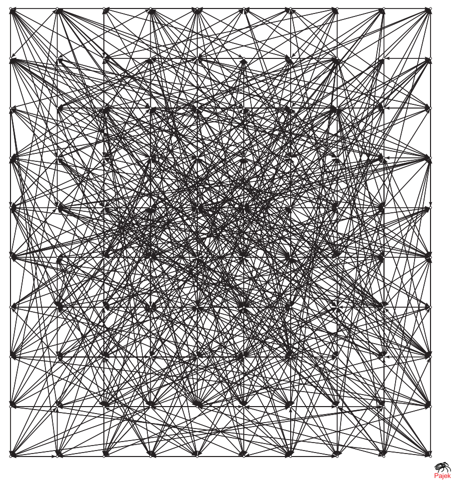

Fig. 3. The social circles network taking into account social distance.

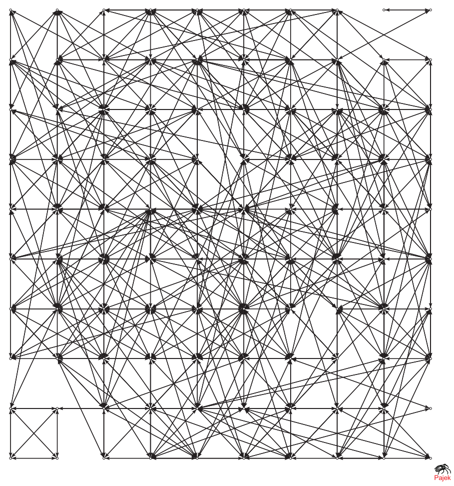

Fig. 4. The social circles network taking into account spatial and social distance.

The other networks were based on the social circles algorithm [14]. All individuals used the same distance size for simplicity, however this varied per network in order to meet the average degree requirement. The social distance was based on Equation 6.

The second network used only spatial distance as the distance measurement (Figure 2).

The third used only social distance as the distance measurement (Figure 3).

The fourth used both spatial and social distance as the distance measurement (Figure 4).

The different social networks have differing clustering coefficients and assortativity on degree (i.e., nodes are connected to other nodes with similar number of nodes [10]) and on node attributes such as age, gender, and activity threshold. These properties are shown in Table I.

V. An illustrative scenario

In this scenario, the only locations present are home locations. This means, that for an activity between two agents, only two locations are possible. Activities were also scheduled for the current time period, however the protocol does allow for looking ahead. For the one activity type and purpose, $\alpha_{home,social}$ was set to 0.5. Each agent has an activity threshold randomly chosen from $[0.5, 1, 1.5, 2.0]$.

The agents all use the same utility function and negotiation protocol. Each agent also has an age level in the range $[1-4]$, which is consistent with the aggregation used in activity-travel surveys (e.g., [18]). The gender similarity is $Q_g = 1$ if two agents have the same gender, and $Q_g = 0$ otherwise. For age, following [18], $Q_a = 4-n$, where n is the difference between the two age classes. The overall similarity or social distance s_{ij} is scaled to $[0, 1]$.

The error term takes into account the location ($N(0, 0.2)$),

Type	Degree	Cluster	Assort (degree)	Assort (threshold)	Assort (age)	Assort (gender)
Random	10.141	0.105	0.036	0.017	-0.021	-0.040
Spatial	10.141	0.509	0.531	0.009	0.069	-0.052
Social	12.040	1	1	0.0112	1	1
Soc/spa	10.505	0.491	0.264	0	0.862	0.565

TABLE I
THE PROPERTIES OF THE DIFFERENT SOCIAL NETWORKS.

each participant ($N(0, 0.1)$), and a personal short- (i.e., drawn every timestep, $N(0, 0.5)$) and long-term (i.e., drawn at the start of the simulation, $N(0, 0.2)$) error.

The model was run for 28 time periods as a warmup, and then for a further 28 time periods to collect data.

The aim of the experiment is to validate the following hypotheses:

- H1. The network structure will affect the number of activities.
- H2. The network properties will affect the number of activities.
- H3. At the node level, the distribution of activities will be different for different input networks and the node attributes (degree, clustering) will affect the number of activities.
- H4. At the relationship level, the distribution of activities will be different for different input networks and the dyad attributes (similarity, distance) will affect the number of activities.
- H5. The interaction protocol will be sensitive to different input networks in terms of the number of successfully and unsuccessfully negotiated activities.

VI. RESULTS AND DISCUSSION

All analysis was done in R, a statistical analysis package. ANOVA tests were used to measure the difference in means of output variables for different input networks, while Kolmogorov-Smirnov tests can indicate whether two distributions are similar. p indicates the significance of each test and r denotes the correlation coefficient. If p is less than 0.05, then this indicates that the result is statistically significant.

A. Hypothesis 1: The overall network structure

The effect of the overall network structure on the number of activities was measured using an ANOVA test. The result suggested a significant difference between the input network types ($p < 0.001$).

This means that hypothesis 1 can be accepted, as the network structure affects the number of activities.

B. Hypothesis 2: The network properties

The correlation between each network property (clustering coefficient, assortativity on degree) and the number of activities was not significant. This indicates that these aggregate measurements are not a good indication of the outcomes of the processes in the system and therefore hypothesis 2 cannot be accepted.

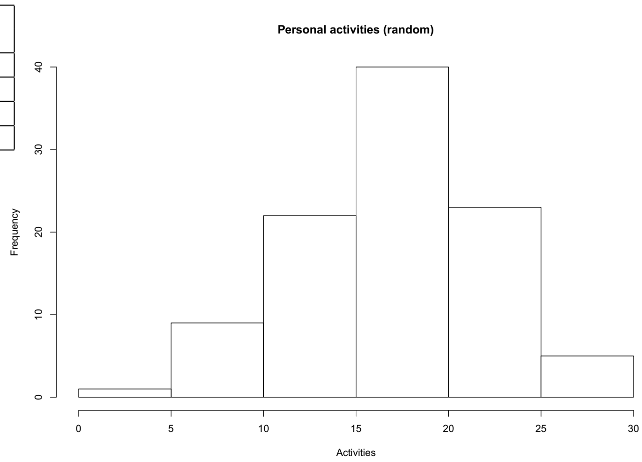

Fig. 5. The distribution of activities for the random network.

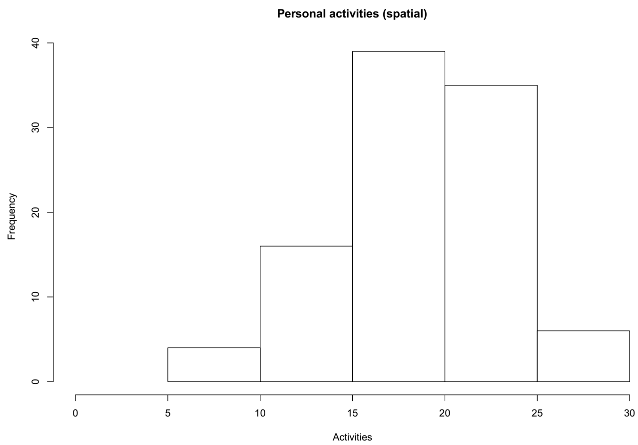

Fig. 6. The distribution of activities for the spatial network.

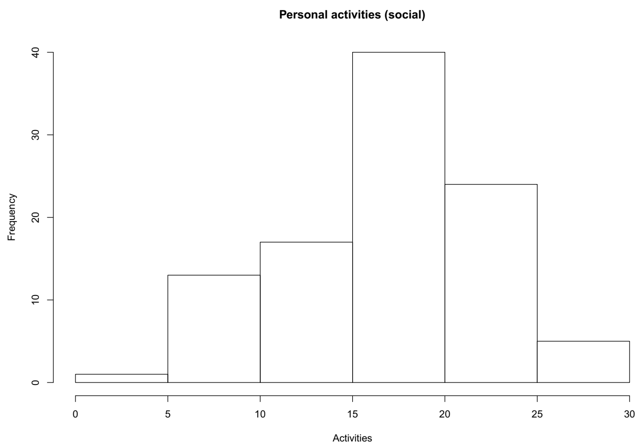

Fig. 7. The distribution of activities for the social network.

C. Hypothesis 3: At the node level

By averaging the number of activities across the ten runs for each person, the distribution of the activities can be measured.

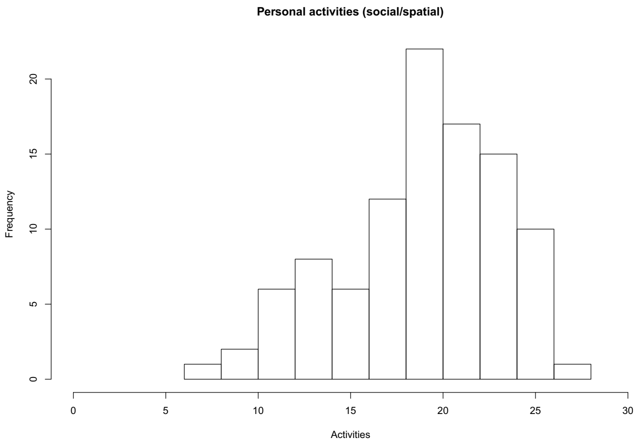

Fig. 8. The distribution of activities for the social/spatial network.

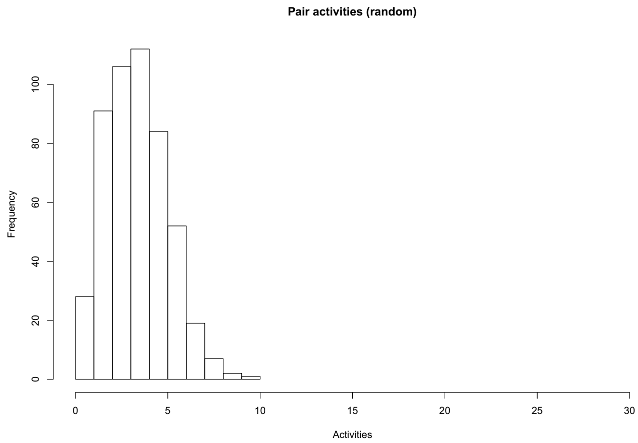

Fig. 9. The distribution of activities per pair for the random network.

Using a Kolmogorov-Smirnov test can indicate whether the distributions are similar or not.

The distributions at the node level are not significantly dissimilar, as shown in Figures 5, 6, 7, 8.

The correlation of the number of activities per person and their centrality or degree is significant ($p < 0.001$, $r = 0.216$). This could be because those with more friends have more opportunity to engage in activities. The threshold for activities is also significant ($p < 0.001$, $r = -0.328$), meaning that those with lower thresholds are participating in more activities as expected. The individual clustering coefficient is not significant, as activities are limited to only two agents. We would expect this to become significant if larger group sizes are modelled.

Although some individual properties are significant, as the overall distribution of activities is not dissimilar, hypothesis 3 cannot be accepted.

D. Hypothesis 4: At the relationship level

As with the personal level, the activities across runs for each pair were averaged. The distributions at pair level were significant (all $p < 0.01$), with the exception of the random network and the social/spatial distance network ($p = 0.70$). The distributions can be seen in Figures 9, 10, 11, 12.

There was a very weak correlation between the similarity of pairs and activities ($p < 0.05$, $r = 0.041$).

The correlation between distance between pairs and the number of activities was stronger ($p < 0.001$, $r = -0.347$), which shows that pairs who live closer to each other are engaging in more activities together.

These results indicate that the relationship level attributes of the network are more significant than the overall or the node attributes and therefore hypothesis 4 can be accepted.

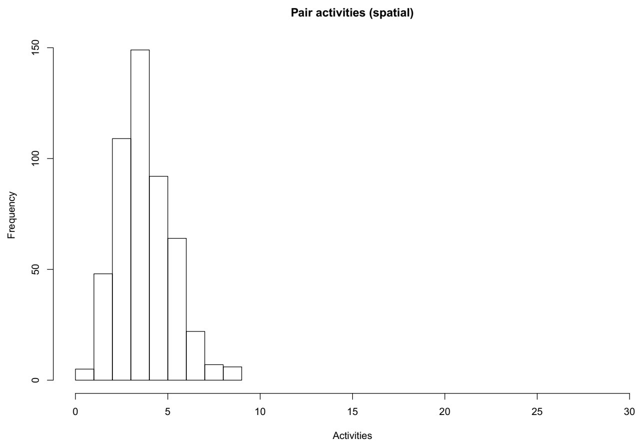

Fig. 10. The distribution of activities per pair for the spatial network.

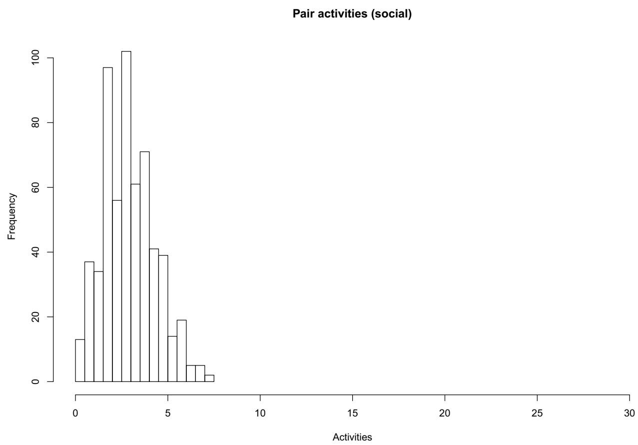

Fig. 11. The distribution of activities per pair for the social network.

E. Hypothesis 5: Performance of the protocol

We expect that the negotiation protocol is sensitive to the network. The protocol can fail at two points: if agents are not available at the same time, or there is no overlap in the preferred activities (e.g., both agents want to do completely different activities, or one does not like any of the options).

We have already shown that the successful activities differs

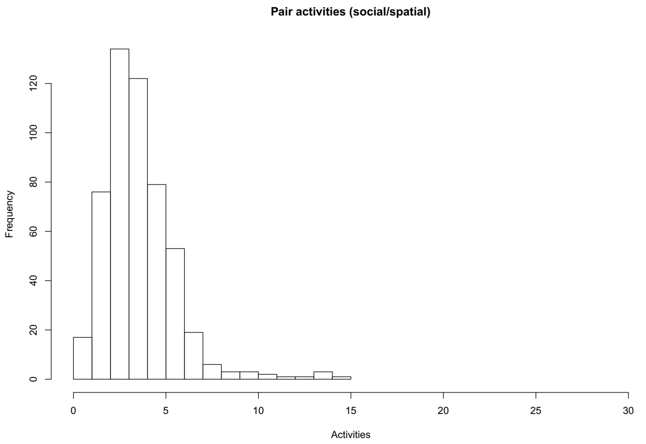

Fig. 12. The distribution of activities per pair for the social/spatial network.

for each network. The unsuccessful activities due to time ($p < 0.1$) and due to activity disagreement ($p < 0.01$) also differs for each network. Table II shows the average for each type.

Network	Successful	Unsuccessful (time)	Unsuccessful (activity)
Random	868.2	834.2	437.5
Spatial	967.5	876.5	178.7
Social	882.7	834.4	405.5
Soc/spa	951.3	868.8	200.7

TABLE II
THE NUMBER OF SUCCESSFUL AND UNSUCCESSFUL NEGOTIATIONS.

The networks with some sort of spatial component performed better; with these networks as a base, agents are less likely to decline an activity based on distance.

From these results, hypothesis 5 can be accepted.

F. Summary

The experiment shows that overall, the key factor is not the overall structure of the network, but the nature of the links between agents.

Whether spatial or social distance is given more weight in the utility function will also influence the outcomes. In this experiment, they were treated equally.

VII. Conclusion

Multi-agent simulation is a useful method for modelling the decision-making processes undertaken by individuals, in this case, regarding whether they participate in a social activity with other people or not. Current research assumes that social networks influence social activities, therefore testing the sensitivity of potential decision-making models to different networks is an important step in evaluating the usefulness of incorporating social networks in activity-travel models. This step could also important for other domains where the social network is influential, e.g., social support networks or exchange networks [25].

We have described an agent-based simulation of social activities and discussed the results of experimentation with several input networks, differing in structure and properties. We show that the relationship properties within the network are more significant than individual or overall network properties for this type of model. However, as the model is developed further, some personal or network properties could become important. For example, people can only maintain a certain number of friends, so the degree becomes important.

The model was simplified to one activity type/purpose and no network dynamics, so that the effects of the input network could be seen. Future work involves extending the model to include further details about activities (including different locations, activities with more than two participants, and taking into account time pressures/value of time), experimenting with agents using different utility functions and/or negotiation protocols, and exploring the effects of social distance/homophily in closer detail, in particular in the context of cultural characteristics.

The results of our research will be used by city planners to evaluate the effects on social activities and travel of both changes in population and their characteristics (e.g., increasing elderly population, an increase/decrease in car ownership) and changes in infrastructure (e.g., public transport routes, locations of new shopping facilities).

As research into the effects of social networks on travel behaviour is in its early stages, there are little data available and as a result most models are in early stages of development. Research into how these models can be validated is in progress [26]. However, this work can be seen as a step forward in the requirements for sensitivity testing of such models.

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